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Representing Causality and Reasoning about Controllability of Multi-level Flow-Systems

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Abstract—Safe operation of complex processes requires that operators maintain situational-awareness even in highly automated environments. Automatic reasoning can support operators as well as the automation system itself to react effectively and appropriately to disturbances. However, knowledge-based reasoning about control situations remains a challenge due to the entanglement of process and control systems that co-establish the intended causal structure of a process.

Due to this entanglement, reasoning about such systems depends on a coherent representation of control and process. This paper explains modeling of controlled processes with multilevel-flow models and proposes a new framework for modeling causal influence in multilevel flow models on the basis of a flow/potential analogy. The results are illustrated on examples from the domain of electric power systems.

Index Terms—Knowledge-based Systems, Means-ends, Power Systems, Intelligent Control, Model-based reasoning, Causality, Functional Modeling

I. INTRODUCTION

Security and safety of technological infrastructures and complex processes requires a thorough understanding of their basic physical principles – and just as much of the control systems enabling their operation.

The interconnection of electric power networks over whole continents creates a complex interdependent setting where incidents in one location may have an effect across continent. The control architecture of interconnected power systems therefore counteracts the propagation of disturbances, for example by activating the resources inside the grid region from which the disturbance originated. The electromechanical process interconnects alternating-current synchronous machines in a large area, but a control architecture established on top of that process modifies the causal structure, thereby reducing dangerous interdependence.

This example illustrates the entanglement between process and control systems with respect to causal explanations. Whereas the connection between causality and control is obvious to control engineers, it is only implicit in typical representations used in design documents. For example, signal diagrams which are common in control engineering are based on a strict input-output notion of causality, but their relation to process diagrams is not explicit and requires insight into the mathematical modeling of the specific controlled process.

Thinking in terms of causality is a basis for human understanding of processes. However, the specific understanding of

how things are causal in a given domain cannot be generalized to other domains. This is one reason why *explicit* representation of causality becomes important when multi-disciplinary and multi-domain systems are employed.

Many developments in electric power systems, particularly the move toward more uncontrolled renewable energy sources and the so-called smart grid, tend toward a deeper integration of different domains of energy [1]–[3], where the overall system efficiency and reliability can be improved. New control approaches and changing control architecture are expected [4]; a much wider range of active devices will require a reformulation of current operation principles, which are based on very limited numbers and kinds of devices, to a more functional description of requirements [5]–[10].

These developments also imply new demands on the manageability and controllability of the overall system. Our ability to study, determine and oversee the behavior of a system depends on our ability to represent and thus to model the system's relevant features. As intelligent control is concerned with the control and supervision of systems, including systems that control other systems, it becomes vital to clearly identify the context of representation (the system-in-view).

Knowledge-based systems have a strength in representing human knowledge and thus also to represent information in context. A central challenge of knowledge-based systems application for critical infrastructures is the the lack consistent representation of processes and their control.

A. Qualitative Representation of Processes, Causality and Control

In this paper we will present a modeling and reasoning approach based on a qualitative model of both process and control systems in a common modeling framework: Multilevel-Flow-Modeling. Multilevel Flow Modeling (MFM) is a process-oriented ontology capturing qualitative functions of material and energy flow processes as well as control functions.

Qualitative representation of processes has some history connected with earlier developments in artificial intelligence. Qualitative Process Theory (QPT) [11] introduced common-sense physics to the description of physical processes. QPT also marked the departure from device-oriented modeling to a process-based abstraction to capture more generic functions of technical processes.

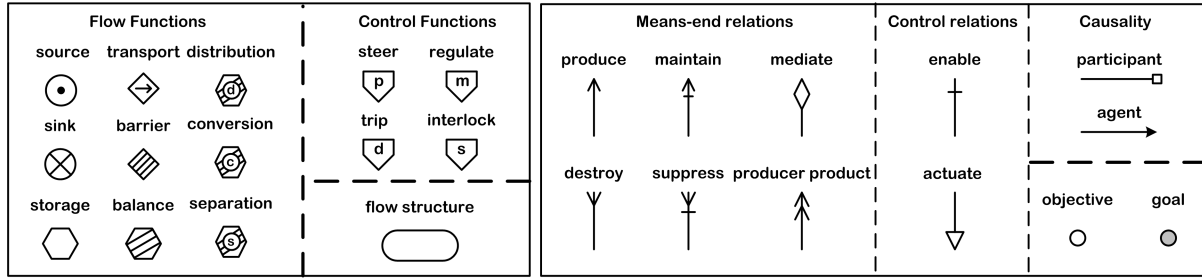


Fig. 1. MFM Entities and Relations.

Representation of material- and energy-flow processes in MFM can be compared to a domain-specific ontology in QPT. The real representational power of MFM, however, comes from its framework of explicit means-ends and part-whole abstractions: Every connected energy- or material-flow is encapsulated in a so-called flow-structure, which then is related with a purpose (an objective, or its function with respect to another flow-structure). These part-whole and means-ends patterns describe the two basic abstractions enabled by MFM. Using basic flow-functions and transformation-rules, a process can always be described in further detail; and using a means-end abstractions, a process-hierarchy, such as a control-hierarchy can be captured.

An explicit representation of causal influence within flow-structures has been considered in MFM since [12] and [13], [14]. In [13] the understanding of causal influence is related to QPT and the need for and practicality of generic causation rules are emphasized.

In this paper, a more rigorous formal basis for modeling and reasoning with MFM is proposed and new agent-roles are introduced reflecting the role of a control agents in the process.

Section II introduces Multilevel Flow Modeling and the relevant background concepts. The results of this work are presented in Section III, introducing tentative roles and the concept for causal influence and reasoning. The method is illustrated on two examples, a power plant and a power grid in Section IV.

II. MULTILEVEL FLOW MODELING

MFM is a functional modeling methodology that provides a library of control functions, energy- or mass-flow-functions and relations, depicted in Figure 1, that can be interconnected to a multi-level representation of causality and intention in flow systems [15]. Adding to the former variety of applications in process engineering, nuclear power plants and others, the field power systems has been developed recently [9], [10]. An MFM model enables situation-dependent reasoning about control situations, by relating system states to system and control objectives.

Applications of MFM include model based situation assessment and decision support for control room operators, hazop analysis [16], alarm design, alarm filtering [17] and planning of control actions [18], [19]. It has been used for knowledge

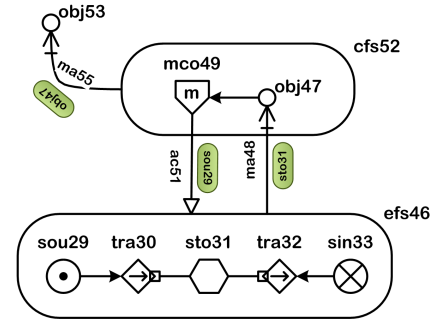


Fig. 2. Example MFM Model with energy flowstructure and control structure. The energy-flowstructure efs46 models a stereotypical balancing process, where both the energy-source on the left and the energy sink on the right influence the storage-level. In this example, the process is balanced by means of a control which aims at maintaining the storage-level by means of actuating the energy source.

representation in AI planning for supervisory control systems [20].

Altogether MFM provides a rich ontology for modeling purpose-aspects of complex processes. MFM is supported by knowledge based tools for model building and reasoning: a graphical modeling environment and a rule-based reasoning environment with graphical user interface (referred to as MFM Workbench in the following).

A. Modeling of Control in MFM

A representation of control systems based on action theory has been added more recently to MFM [15], [21], [22]. The four elementary control functions, which are based on elementary action types, are found in Figure 1.

In contrast to the classical signals and systems perspective, control functions have a special role in the perspective of mean-ends modeling: Whereas a 'flow-structure' is a functional abstraction of a process, the 'control-structure' is a representation of the *intentional structure* realized by a control system¹. This distinction becomes essential when reasoning about control systems.

An example model of a control structure and a related flow-structure is given in Figure 2:

¹In the control literature, the 'intentional system' is sometimes referred to as 'active' structure, whereas the controlled system, here '(multi-level) flow-structure', is referred to as the 'passive' basis. This wording does not apply exactly for multilevel-flow-structures, as energy sources and sinks may well be part of the system.

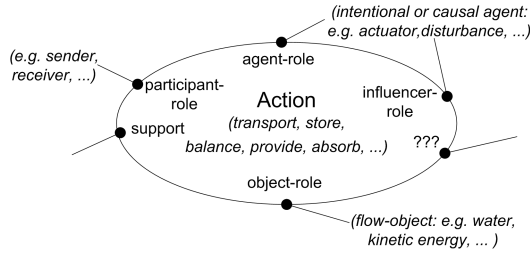


Fig. 3. Action-roles define the participants of an action. Depending on the function and context the roles considered necessary vary.

- *Control-objective* **obj47** and *control function* **mco49** are encapsulated in a *control structure* **cfs52**.
- Requirements to the performance of the control are formulated as an objective associated with the control structure (*performance objective*, **obj53**).
- The control objective is associated via a *means-objective-relation* with the *mainfunction* (here **sto31**), the state of the mainfunction is subject of control.
- The control function is connected to the flow-structure via an *actuation-relation*, **ac51**, targeting **sou29**.

In [9], [10] the authors have shown how this modeling of control can be applied to power systems.

B. Functional Roles

In [14], the connection between the symbolic representations of functions and the semantics of actions have been elaborated:

Definition 1 (Function). *A function of an entity E which is part of a system S , is specified in terms of the role R of E in relation to an action describing and intended state-change in S .*

Functions model interconnected actions or action-primitives. The actions can be associated with a “semantic deep structure” [14], defining roles of an action as slots that can be filled, which is illustrated in Figure 3.

This understanding of a function as an action with a semantic deep structure implies that a number of roles can be associated with each function, such as *agent*- and *object*-roles. Further, the action-metaphor is deeper than the flow-metaphor, and potentially enables extension of MFM to other domains of representation if necessary.

Flow-structures are an interconnection of actions with a common flow-object.

Definition 2. (*Flow perspective* [14]) *The flow perspective on an action describes the state change that the object is undergoing without reference to the agent involved.*

Flow-functions are formulated in the flow perspective of the actions modeled. A relation between two function-structures therefore also marks a perspective-shift, in which for example the flow-object of another structure turns into an external agent of the related function [3], [23]. As will be shown later, external agents influence the causal structure of a process, and

such agents can also be attributed to flow-functions on the basis of control-considerations.

C. Causality in Flow-models and Causal Reasoning

Fundamental to the understanding of causality in MFM flow-structures is the notion of agency. *Causal roles*, as introduced by [14], express the influence that a state of a flow-function has on the flow associated with an adjacent transport function. The role is always marked at the transport-side of a connection-line between two functions, ending with a box (participant-role) or with an arrow (agent-role) (shown in Figure 1, on the right: Causality).

A flow-perspective enables causal reasoning over flow-systems, in order to predict consequences or to find possible root-causes of a state-change in the system. This concept of fault diagnosis with MFM was presented in [12], and extended with explicit causal agency in [13], [14]. MFM-based root-cause analysis has been applied for diagnosis and used in commercial applications for alarm filtering.

In past implementations, the causal propagation logic considered interactions between function-pairs, but did not include the role of control agents. In the following, the causal roles introduced in [13] will be utilized, but the logic of influence will be condensed to more rigorous syntactic rules.

III. REPRESENTING CAUSALITY AND CONTROL

Even though the larger part of this paper will focus on reasoning about causality within flow-structures, it is important to emphasize the larger perspective that modeling with MFM provides, especially for the modeling of controlled processes.

MFM facilitates the definition of the roles a control system may take with respect to a process (more in Section III-A), as well as the different types of requirements that need to be formulated for a process.

The development of the causal reasoning framework is based on an extension of MFM introducing flexible agent-roles in Section III-B. The main result of this work, causal pattern classification and causal path reasoning, is presented in Section III-C. Finally, Sections III-D and III-E present the implemented algorithm and a link to controllability.

A. Control as Disturbance Encapsulation

In a means-ends framework, control structures can be understood as fact-producers, that is, they transform a goal (intention Z) into an observable fact (result Z), see Figure 4. In closed loop control, the control system is supplied with information about deviations from the objective, which enables the rejection of influences contrary to the control objective. In an agent-perspective, a successful control agent has the ability to ‘overpower’ this disturbance agent (successful encapsulation).

Control design anticipates disturbances and equips the controller with sufficient control resources to defeat expected

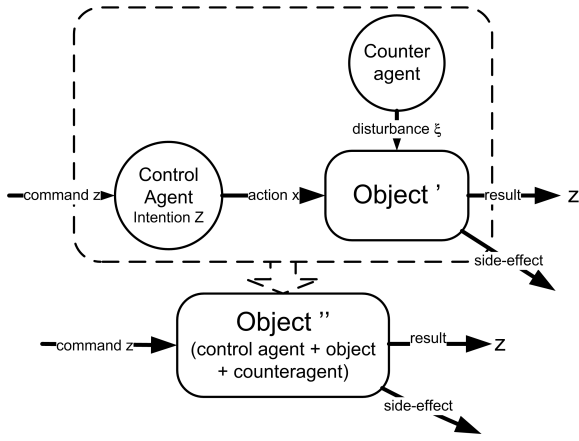


Fig. 4. Encapsulation of disturbance by a control agent. The introduction of a control agent implicitly models a virtual counter-agent.

disturbances. Figure 4 illustrates this concept of control as disturbance encapsulation².

Complex processes are usually composed of several levels of such encapsulation. A higher-level system acts on an encapsulated system, without a need to consider the disturbance that has been encapsulated. This leads to the notion of *execution levels*. A typical example is a cascaded control system, where the lower-execution level receives an input signal as control reference, and a higher level systems perceives the closed loop of the lower level systems again as dynamical input-output structure. Depending on the level of abstraction, subordinated control loops need not be represented explicitly. The modeling of the feedwater pump control in Example 1, Section IV-A, is another example for this situation.

Reasoning about control levels thus requires a representation of this encapsulation. A necessary condition for this reasoning is thus to frame the causality at the right level of abstraction. For the remainder of this paper we focus on the representation of causality that forms one control level.

B. Introduction of External-Agent Roles

As outlined above, the action-perspective allows a straightforward extension of multilevel-flow-models to attribute external roles. In the context of control, we establish three new roles capable of influencing the state of a function: Actuator, Disturbant and Conservant, as shown in Figure 5 a). Figure 5 b) illustrates the use of these roles in a simple MFM example, analog to Figure 2.

An *actuator* performs the commands it receives from a control agent (control function). Therefore it needs to be equipped with a reference to the actuation-relation (multiple roles may refer to the same actuation-relation). It can also be parameterized with a control-range, but quantitative aspects will not be considered in this paper.

²The term “disturbance rejection” of control engineering is equivalent, but supposes a control-perspective. In a process-perspective, successful control actions render the respective disturbance irrelevant.

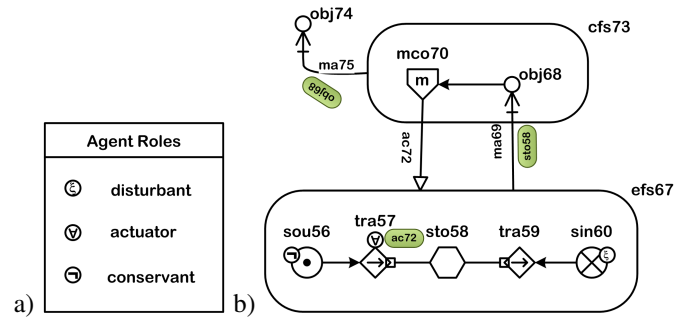


Fig. 5. a) New *External-Agent-Roles*. b) MFM model, based on Figure 2 with attached roles. Here, the *disturbant* corresponds to load variations, the *conservant* corresponds to a setpoint for the source-potential, and the *actuator* is influencing, not determining, the flow through tra57.

A *disturbant* represents a disturbance, i.e. the role assumed by the counter-agent. It may also be parameterized with a quantitative information.

The third role-entity, the *conservant* ensures that the variable, which a control agent would have manipulated through an actuator, is kept static, like a fixed setpoint.

The roles can be attached to these flow-functions (refer to Figure 1 for the complete set): *Source*, *Sink*, *Transport*. Attachment of a role means that a free variable of the respective function is now determined by the external agent who is represented by the role. This also means additional influence on the state-variable associated with a given function is noted, which changes the causal pattern of the function, as seen in the next section.

Storage and *Balance* do not accept an external role – there are no free variables. The other flow-functions have not been considered yet.

C. Patterns for Causal Reasoning

In this section a notion of causality is developed that is suitable for multilevel-flow-models and the modeled processes, but also consistent with underlying physical concepts. It should be noted that, similar to the notions developed in QPT, flow-functions have been defined from intuitive and generic process-engineering notions rather than from physical laws.

The reasoning system classifies patterns within the flow-structures of the MFM model and associates state-variables to the flow-functions.

1) *Introduction of State Variables*: In order to introduce a logic of influences, we will introduce state-variables to the flow-functions, dependent on the causality pattern surrounding them.

Two types of state variables are introduced: *e-/m-flow* (f) and *potential* (v), corresponding to the analogies: mass-flow and mass, as well as energy-flow (power) and energy (content).

The analogy is intuitive, considering an energy-flowstructure: We associate an *energy-flow* with every transport function and a *potential* with every storage function.

For the remaining functions, the state-variable assignment depends on the surrounding function pattern.

Flow - Causal template-	Influence on flow: Upstream Downstream External agent			Causal Tag	Formula template
	—	—	✓	FDEFA	$f_i = f_A$
	✓	—	✓	FMANUP	$f_i = k_A v_{up}$
	—	✓	✓	FMANDO	$f_i = k_A v_{do}$
	✓	✓	✓	FMANBAL	$f_i = k_A * (v_{up} - v_{do})$
	—	—	—	FBS	—
	✓	—	—	FDEFUP	$f_i = f_{up}$
	—	✓	—	FDEFDO	$f_i = f_{do}$
	✓	✓	—	FBAL	$f_i = k_{tr} * (v_{up} - v_{do})$

Fig. 6. Classification of causal templates. The templates are differentiated by the origins of influence on their flow: upstream, downstream or external agent.

2) *Causal Context of Transport functions*: The modes of causation in a MFM-flow-structure are centered around transport-functions, which represent the energy- or mass-flow between any two non-transport functions. The table in Figure 6 lists eight templates that imply a different causal context. Eight, because there are two sides of a transport (*upstream* or *downstream*) with two possible roles each (*participant* or *agent*), and in addition, there may or may not be an *external agent* associated with the function. External agents can be roles, as introduced in the previous section, or a means-function relation: *producer-product* or *mediate*.

The logic behind this classification is apparent: If only one agent is present, it defines the flow in the transport function (FDEFA, FDEFUP, FDEFDO). If there are two causal agents, the flow has to be established from a difference in the potentials of the connected flow-functions (FBAL); in addition, the rate of this flow-exchange can be manipulated by an external agent (FMANBAL). The third and last case is derived from the FMANBAL case, but it requires the definition of a neutral potential (FMANUP, FMANDO). Finally, patterns with the the causal tag FBS cannot be accepted for causal reasoning, because there is no causality assigned.

All cases can be illustrated on the examples of connected water-tanks. FDEFA: A pump between two tanks is moving water from one tank to another. FDEFUP, FDEFDO: A water-source, or sink, possibly driven by a pump that would be external to the system-in-view. FBAL, FMANBAL: the classical interconnected tanks, possibly with a valve in the connecting tube. An example of the last case (FMANUP, FMANDO) would be water that is flowing from an outlet at the bottom of a tank - the flow-rate can be manipulated by a valve, but it is also dependent on the water-level.

To present a mathematical analogy of these causal influence

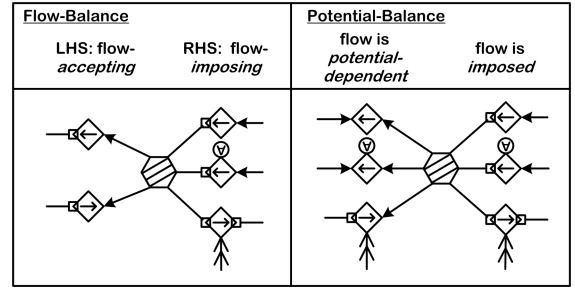


Fig. 7. There are two possible cases for a balance: Flow-balance and Potential-balance. For each type of influence there are example-transport-functions, for the acceptable patterns (causal tags).

situations, we associate flow-variables f , v for potentials and k to indicate a rate-parameter. The equations on the rightmost column of Figure 6 indicate the analogy. Note that the state of the transport, f_i , is always the result of causation. It can either be imposed directly, or result from a potential difference of adjacent functions, moderated by a rate-factor. The potential-rate model corresponds to a constitutive equation (such as Ohm's Law).

Based on these templates, state-variables can be assigned to neighboring adjacent sources and sinks: For a FDEFUP-(FDEFDO-) transport, an adjacent source (sink) is assigned a *flow-state*, in all other cases a *potential*.

3) *Flow- and Potential-Balances*: For Balance functions, the causal context is analyzed and two types of balances are identified:

- *Flow-balance*: Pre-assigned causality. A number of flows is imposed (RHS) and are summed up, which defines the flow through the balance: noted in the intermediate flow-variable f_{bal}^* .
- *Potential-balance*: Partly a-causal. Flow is a result of potential differences across the balance and the respective transports. The Balance is assigned an intermediate potential v_{bal}^* , analog to hydrodynamic pressure.

The patterns that establish either kind of balance are illustrated in Figure 7. For the flow-balance, a minimum of one connected RHS transport, a transport for which the balance is only *participant*, is required and the LHS requires exactly one FDEFUP/FDEFDO transport if the flow-direction is always the same, or a second transport with opposing flow-direction. The potential-balance has the same requirement for the RHS (with defined causality), but has a no directly resulting flow.

In case of the *flow-balance*, the causality structure is that of input-output: a flow-*input* (RHS: right-hand-side) defines flow-*output* (LHS: left-hand-side). This can be formulated as

$$f_{tr,LHS} := f_{bal}^* := \sum f_{tr,IN,RHS} - \sum f_{tr,OUT,RHS} , \quad (1)$$

where f_i refers to the flow-variable associated with the respective function i of the LHS- or RHS-category of this balance. The resulting flow f_{bal}^* is imposed on the LHS transport(s), depending on directionality. This may be formulated as fol-

$$f_{tr,OUT,LHS} = \lfloor f_{tr,LHS} \rfloor_0 \quad \text{and} \quad f_{tr,IN,LHS} = \lceil f_{tr,LHS} \rceil_0^0 \quad (2)$$

A *potential-balance* is a-causal for a part of the connected flows. The flow through the balance is a result of the total potential difference across the balance, so the intermediate-potential at the balance v_{bal}^* is required to determine the flow. In addition, there may be flows imposed to the balance, analog to the RHS of a Flow-balance.

$$(\sum k_{Tr,UP,i} - \sum k_{Tr,DO,i})v_{bal}^* := \quad (3)$$

$$(\sum k_{Tr,UP,i} v_{UP,i} - \sum k_{Tr,DO,i} v_{DO,i}) \quad (4)$$

$$+ \sum f_{tr,IN,RHS} - \sum f_{tr,OUT,RHS} \ , \quad (5)$$

A network of potential balances corresponds to a linear vector-equation, similar to the load-flow equation of an AC electricity-network, with a potential-balance assigned to each bus. For a linearized power-flow equation, the 'intermediate potential' v_{bal}^* would correspond to the bus voltage angle variation $\Delta\theta_{bus}$ (illustrated in Example 2, Section IV).

The causal-reasoning system aims at generating a causal path from assigned external agent roles to the objective, that is, to the function associated with this objective (*mainfunction*).

- 1) Analyze causal patterns in all flow-structures in the MFM model: Causal tagging of transports, assignment of state-variables and pattern-identification for flow-/potential balances.
- 2) Initiate: Which control objective is to be traced? The control objective becomes root of the *influence-tree*.
- 3) Generate *influence-tree* for the selected control-objective. Using propagation-rules based templates and patterns identified previously, a tree-structure is generated which notes all possible influences from the model.
- 4) Trace *causal paths* in influence tree.

the fulfillment of the objective and *b*) a direct path of influence for each external-agent role with influence on the state of the mainfunction (*causal path*). This reasoning principle will be illustrated in Example 1.

The concept of controllability is fundamental to control engineering, as it formulates a necessary condition for controlling a system. A full analysis of this concept would be beyond the scope of this paper, but we may reflect on the properties of flow-structures.

State controllability: A dynamical system is called completely controllable if an external input can move the state of the system from any initial state to any other final state in finite time.

We do understand *inputs* as assigned actuator-roles and *outputs* as the states of the mainfunction associated with the control-objective. The “system” could be considered exactly those functions that are part of the influence-tree.

Under certain -limiting- conditions, there is a mapping to output-controllability: a) there are no causal loops in the system b) there is only one actuator in the tree.

A detailed study of the graph properties of flow-structures and their mapping to linear systems could generate further structural sufficient conditions for controllability.

The modeling and reasoning principles shall be demonstrated on some examples. The first example highlights the multi-level physical representation aspects of the modeling approach on a simplified power-plant. The second example

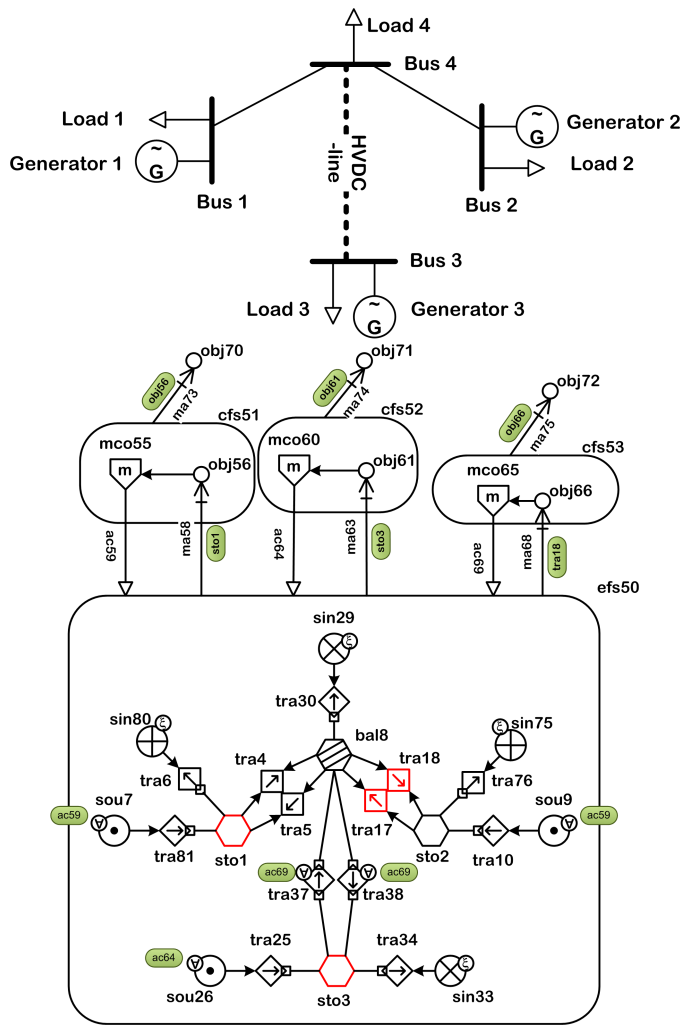


Fig. 10. One line diagram and MFM model, illustrating the network modeled in Example 2. Note the combination of two AC networks (synchronous areas) with a DC link. In the MFM model, mainfunctions associated with the control objectives are marked in red.

conceptual model introduces flow- and potential variables to make sense of the influence patterns modeled by the causal roles of an MFM model. Based on this idea, syntactic rules for function-causality configurations have been derived.

The concepts have been implemented in a software-framework which enables graphical modeling and model-based reasoning for artificial intelligence applications.

The method has been demonstrated on two energy systems examples. It has been shown that the modeling approach readily maps into the domain-specific physical frameworks.

Further we have outlined, how the causal-path concept introduced in this paper is related to the controllability concept of control engineering. A flexible assignment of agent roles allows the re-use of models and restructuring of control-loops and objectives on a given process-model.

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